Cities 158 (2025) 105664

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Shared micromobility in multimodal travel: Evidence from three European cities

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A R T I C L E I N F O

Keywords:
Shared micromobility
Multimodality
Modal integration
Multimodal transport system
Travel pattern

A B S T R A C T

Shared micromobility (SMM) has the potential to be integrated into multimodal transport systems in various urban contexts. However, its interaction with other transport modes in individuals' daily travel is not well understood. Accordingly, this study investigates how people use different forms of SMM in conjunction with existing transport modes in three European cities with different urban settings and mobility systems (Utrecht, Greater Manchester, and Malmö). The findings suggest that the usage combination of SMM and existing transport modes varies both within and between cities. Using latent class analysis, we identified four travel patterns in each city. Overall, travellers who use SMM modes more frequently exhibit more multimodal travel patterns, but the combination of modes depends on the city's modal share. Specifically, frequent SMM users use various existing transport modes more frequently; occasional SMM users more often use private micromobility and one or two existing modes; non-SMM users typically use one or more existing modes predominantly. The comparisons of user characteristics across different travel patterns within each city show that individuals' travel patterns mainly differs in their personal demographic characteristics and personal travel attributes (i.e. what vehicles and mobility tools they have) but less so in the spatial characteristics of their residential neighbourhoods. The findings of this study suggest that tailoring SMM services to specific urban contexts will better integrate SMM into existing transport systems and meet the needs of different traveller groups.

1. Introduction

Multimodality, the use of multiple transport modes within a certain time period (Nobis, 2007), has been considered as an essential approach to reducing car dependence and alleviating related environmental and social problems (Buehler & Hamre, 2015; Diana & Mokhtarian, 2009). On the one hand, multimodality is believed to decrease energy consumption and carbon emissions by substituting car trips with alternative modes (Heinen & Mattioli, 2019a, 2019b); on the other hand, multimodality is believed to increase mobility and accessibility by providing individuals with the advantage of potentially using various transport options (Frank et al., 2021; Makarewicz & Németh, 2018). However, multimodal travel is often not simple because, compared to monomodal travel, it requires the skills and knowledge to use multiple transport modes, as well as a better ability to procure travel information and organize travel time (Liao et al., 2020; Nobis, 2007). Furthermore, for certain population segments, multimodal travel may not be possible due to the low availability of travel options or lack of skills (Alonso-González et al., 2020; Fu et al., 2024). Therefore, despite the promising environmental and societal outcomes of a shift towards more multimodal passenger mobility, multimodality can be effortful for individuals to realise (Döge & Abraham, 2020), which poses a paradox for cities wishing to promote multimodal travel policies.

In recent years, innovations in transport services (e.g., shared mobility, ride-hailing services, Mobility as a Service) have made transport options more accessible and travel information more obtainable, thereby unlocking new opportunities for multimodality. Shared micromobility (SMM) has rapidly gained popularity in the past years in many regions around the world (Montes et al., 2023; Oeschger et al., 2020). Studies have found that different forms of SMM, including (dockless) shared bikes, shared e-bikes, shared e-scooters, and shared e-mopeds, are changing the way people use existing transport modes (Bieliński et al., 2021; Reck et al., 2021; Reck et al., 2022). SMM has been found to be particularly useful for "first- and last-mile" solutions and is therefore often used in conjunction with public transport (Vinagre Díaz et al., 2023; Yan et al., 2023). Previous studies have found that electric-powered SMM modes, such as shared e-scooters and shared e-bikes, have replaced short-distance car or transit trips in certain contexts (Choi

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https://doi.org/10.1016/j.cities.2024.105664
Received 5 May 2024; Received in revised form 21 October 2024; Accepted 9 December 2024
Available online 24 December 2024

et al., 2023; Meng et al., 2020; Vega-Gonzalo et al., 2024; Wang et al., 2023), thereby changing the relative share of car and transit usage for certain SMM users. Accordingly, SMM shows its potential to act as a multimodal alternative and may be an effective tool to promote multimodality.

The potential for SMM to integrate into existing transport systems may vary depending on the road environments and regulations in different regions. Studies have highlighted factors that discourage potential riders, with the main obstacles being safety concerns stemming from sharing roads with motor vehicles and the lack of dedicated cycling facilities (Badia & Jenelius, 2023; Teixeira, Diogo, et al., 2023). Therefore, in many cities, especially those with car-oriented road environments, people face barriers to using micromobility, which may lead to lower usage of micromobility and hinder efforts to promote SMM. While in cities where cycling facilities are more sufficient and road environments are more strictly regulated to protect cyclists (e.g. a wider range of motor vehicle speed limits), promoting and integrating SMM into existing transport systems may be more feasible.

Studies across various regions have examined the potential of SMM as a part of multimodal mobility solutions by exploring its interaction with existing transport modes (Oeschger et al., 2020; Zhan et al., 2023; Zhang & Liu, 2021). These studies have investigated the competition or complementarity between SMM and a certain transport mode by comparing how travellers use SMM versus another mode (Bieliński et al., 2021; Vinagre Díaz et al., 2023), and the research evidence shows that SMM usage and their interplay with other transport modes vary in different urban settings and mobility systems. For example, in areas with lower population density and higher car dependency, such as many cities in the US and Canada, shared e-scooters, and several other modes of SMM, have been found to primarily replace taxi/ride-hailing, walking, and short-distance car-driving trips (Lee et al., 2021; Wang et al., 2023). In areas with higher population density where public transport and private micromobility are more common, such as many European cities, SMM, in various forms, has been found to primarily replace walking and cycling (private bike) trips, as well as short-distance transit trips (Christoforou et al., 2021; Nikiforiadis et al., 2021; Weschke et al., 2022). Studies based in various urban contexts have found that SMM could complement (long-distance) transit trips (Fan & Zheng, 2020; Ma et al., 2022; Zhan et al., 2023). Regional differences in the interaction between the use of SMM and existing transport modes suggest that the potential of SMM to facilitate multimodality may vary in different urban contexts.

SMM has rarely been assessed as a component of multimodal travel to investigate its interaction with multiple transport modes simultaneously (Badia & Jenelius, 2023). Consequently, little is known about the role of SMM in multimodality and individuals' daily mobility (as a whole). To uncover the potential of SMM in the promotion of multimodality, it is imperative to consider SMM as a multimodal alternative and comprehensively analyse its interactions with a variety of existing transport modes (Lee et al., 2021). Therefore, this study aims to contribute to a comprehensive knowledge of SMM in multimodal passenger mobility by answering the following research questions:

Q1: In what ways is SMM used in conjunction with other transport modes, and what are the differences between travel patterns with and without SMM?

Q2: How do the user characteristics vary across travel patterns within each city?

Q3: How do the travel patterns and their user characteristics differ across cities?

The analysis is based on three European cities with different urban settings and mobility systems, namely Utrecht (the Netherlands), Greater Manchester (the UK) and Malmö (Sweden). Using latent class analysis (LCA), we identified specific patterns of modal combinations within each city. The analysis included SMM users and non-users to compare their travel patterns, and specifically compared the interactions between SMM and existing transport modes across cities. We then compared the user characteristics across different travel patterns within and between cities, considering the city's urban setting, mobility system and road environment. The results may provide policymakers and practitioners with insights into what specific patterns of multimodality can be encouraged through the implementation of SMM, how to better integrate SMM into existing mobility systems to support multimodal travel (Badia & Jenelius, 2023), and how to tailor the interventions to different traveller segments (Dacko & Spalteholz, 2014).

2. Literature review

In this section, we first review papers on the availability of transport modes and multimodal travel behaviour to explore the possible relationship between an extended transport option set and multimodality. We then review papers on the modal shift from existing transport modes to SMM to explore the possible interactions between SMM and existing transport modes.

2.1. Extended transport option set and multimodality

Studies have investigated the relationship between the availability of different transport modes and individuals' multimodal travel behaviour. Individuals who have better access to public transport, own a personal bike, and have a public transport season ticket have been found to be more multimodal compared to their counterparts (Buehler & Hamre, 2015; Circella et al., 2019; Fu et al., 2024; Heinen & Chatterjee, 2015). This suggests that more available transport options may increase individuals' level of multimodality.

Several studies measured the changes in multimodality over time. Scheiner et al. (2016) used German Mobility Panel data to study intrapersonal changes in multimodality over two years, and they found that an improvement in public transport accessibility increased multimodality. Klinger (2017) studied the interdependences between intrapersonal changes in multimodality and residential relocations, and he found that moving to a more public transport or cycling-friendly city was associated with a higher overall probability of combining certain travel modes and being more multimodal. A Canadian study also found that at the regional level, increasing public transport supply (in terms of the number of bus stops) could increase the multimodal level of residents in the area (Deschaintres et al., 2021). The above longitudinal evidence further suggests that an improvement in the availability of transport options may increase multimodality.

Unlike other modes, car availability shows an inverse association with multimodality. Studies have found that people who hold a driver's license and/or have better access to cars are more likely to be monomodal car users (Buehler & Hamre, 2015; Heinen & Chatterjee, 2015). Scheiner et al. (2016) and Klinger (2017) both found that an increase in car availability was associated with a shift to less multimodal behaviour, and Scheiner et al. (2016) also found that reduced parking space increased multimodality over time.

In addition to the possible positive effects of an extended transport option set (other than cars) on multimodality, studies also found multimodality may, in turn, induce the use of a newly available transport option. Kroesen and Van Cranenburgh (2016) found that multimodal travellers were more likely to switch from one travel pattern to another over time. Heinen (2018) found that multimodal travellers had a higher intention of changing their travel behaviour, presenting as decreased car use. These findings indicate that people who are already multimodal may be more likely to adjust their travel patterns and adopt new transport options, such as SMM, to replace previously used modes. Similar results have been presented in other recent studies that people who live multimodal lifestyles have a higher propensity to use SMM as an alternative to their daily travel (Mohiuddin et al., 2024; Raux et al., 2017).

2.2. Interactions between SMM and existing transport modes

Research on the user behaviour of SMM has mainly focused on the following topics: 1) *the user characteristics of SMM* (Mohiuddin et al., 2024; Reck & Axhausen, 2021); 2) *the usage patterns of SMM* (*when, where, for what*) (Ross-Perez et al., 2022; Sherriff et al., 2020); 3) *the motivations for SMM adoption and usage* (*drivers and barriers*) (Aguilera-García et al., 2020; Krauss et al., 2022); 4) *the determinants of SMM usage patterns* (Aguilera-García et al., 2024; Li et al., 2020); and 5) *modal shift* (Weschke et al., 2022; Yan et al., 2023). Among these research topics, *modal shift* is most relevant to multimodality because it usually explains the interactions between SMM and other modes of transportation by measuring changes in the use of other transport modes after the adoption of SMM (Bieliński et al., 2021; Mohiuddin et al., 2023). There are two main patterns of interactions between SMM and other transport modes: *substitution* and *complementarity*. Substitution refers to SMM replacing the use of an existing transport mode; whereas complementarity is that SMM supports the use of another transport mode, for example, as a feeder mode to connect public transport (Wang et al., 2023). Research findings differ across the forms of SMM and the contexts of specific study areas (Table 1).

In terms of *substitution* relationships, walking and local public transport (including bus, tram, and metro) are most often substituted by different forms of SMM, especially electric-powered SMM modes (Wang et al., 2023). Walking was found to be replaced by varying forms of SMM in Europe, North America, and Asia-Pacific (Campbell et al., 2016; Mitra & Hess, 2021; Weschke et al., 2022). Specifically, shared e-scooters have been found to replace walking and public transport in most North American cities (Kim et al., 2023; Luo et al., 2021; Ziedan et al., 2021), while only found in a few European cities (Reck et al., 2022; Weschke et al., 2022). Shared bikes and shared e-bikes have been reported to replace public transport in many European cities (Ma et al., 2020; Roig-Costa et al., 2024; Teixeira, Silva, & Moura e Sá, 2023), but similar substitution is less common in North American cities.

In many European cities and Beijing, China, shared bikes and shared e-bikes have been found to replace the use of private bikes (Campbell et al., 2016; Reck et al., 2022; Roig-Costa et al., 2024), while North American studies found little evidence of SMM substituting private bikes. In contrast, driving (personal or household cars) and the use of taxi/ride-hailing have been found to be replaced by SMM modes in most North American cities (Fukushige et al., 2021; Guo & Zhang, 2021; Kim et al., 2021), while only in a few European cities shared bikes have been found to replace car use (Raux et al., 2017). These differences can be attributed to the limited cycling culture and high car dependence in North American cities.

In terms of *complementarity* relationships, where travel becomes more multimodal by definition with the addition of SMM, public transport was the only transport mode found to be complemented by SMM modes, and this is true across regions. In several North American cities, shared e-scooters were found to support bus and metro systems (Ma et al., 2022; Yan et al., 2023; Ziedan et al., 2021). In European cities, various forms of SMM including shared bikes, shared e-bikes, shared e-scooters, and shared e-mopeds have been found to support public transport systems including buses, trams, and metros, as well as trains (Bieliński et al., 2021; Koglin & Mukhtar-Landgren, 2021; Montes et al., 2023; van Kuijk et al., 2022). In two Asian cities, shared bikes were found to complement the metro/subway system (Fan & Zheng, 2020; Kim, 2023). As a supplement to public transport, SMM modes were found to primarily support first- and last-mile travel and also serve as an alternative in areas with low transit line coverage (Vinagre Díaz et al., 2023).

The substitution and complementarity relationships between SMM modes and existing transport modes differ not only at the inter-city level but also at the intra-city level. Studies found that such interactions vary in traveller groups with different personal characteristics and living in different areas within a city. Younger people were found more likely to

Table 1
An overview of the literature on the substitution and complementarity effects of SMM.

	SMM modes	Substituted modes	Complemented modes
Europe			
Barcelona, Spain (Roig-Costa et al., 2024)	Shared bike	Walking Private bike Public transport (metro, bus)	
Lisbon, Portugal (Teixeira, Silva, & Moura e Sá, 2023)	Shared bike	Public transport	
Rome, Italy (Vinagre Díaz et al., 2023)	Shared e-scooter	Public transport (metro)	Public transport (metro, train)
Rotterdam, the Netherlands (Montes et al., 2023)	Shared bike		Public transport (metro)
	Shared e-moped	Public transport (metro)	Public transport (metro)
Germany (Weschke et al., 2022)	Shared e-scooter	Walking Public transport	
Utrecht, the Netherlands (van Kuijk et al., 2022)	Shared bike		Public transport (bus/tram)
	Shared e-bike		Public transport (bus/tram)
	Shared e-scooter		Public transport (bus/tram)
Zurich, Switzerland (Reck et al., 2022)	Shared e-bike Shared e-scooter	Private bike Public transport Walking	
Lund, Sweden (Koglin & Mukhtar-Landgren, 2021)	Shared bike		Public transport (bus)
Tricity, Poland (Bieliński et al., 2021)	Shared e-bike	Public transport	Public transport
Delft, the Netherlands (Ma et al., 2020)	Shared bike	Walking Private bike Public transport (bus/tram)	Public transport (train)
Lyon, France (Raux et al., 2017)	Shared bike	Walking (Private) Car	Public transport
London, the UK (Fishman et al., 2014)	Shared bike	Walking Public transport	
North America			
Washington D.C. and Los Angeles, the US (Huang et al., 2024)	Shared e-scooter		Public transport
Washington D.C. and Los Angeles, the US (Yan et al., 2023)	Shared e-scooter	Walking (Private) Car Taxi/Ride-hailing	Public transport (bus, metro)
Portland, the US (Kim et al., 2023)	Shared e-scooter	Walking Public transport (Private) Car	
Washington, D.C., the US (Ma et al., 2022)	Shared e-scooter		Public transport (metro)
New York, the US (Lee et al., 2021)	Shared e-scooter	Car-pooling	
Sacramento, the US (Fukushige et al., 2021)	Shared e-bike	Walking (Private) Car	
Indianapolis, the US (Luo et al., 2021)	Shared e-scooter	Walking Public transport (bus)	
Nashville, Tennessee, the US (Ziedan et al., 2021)	Shared e-scooter	Public transport (bus)	Public transport (bus)
Tampa, Florida, the US (Guo & Zhang, 2021)	Shared e-scooter	(Private) Car Taxi/Ride-hailing	

(*continued on next page*)

Table 1 (*continued*)

	SMM modes	Substituted modes	Complemented modes
Toronto, Canada (Mitra & Hess, 2021)	Shared e-scooter	Walking Public transport	
Washington, D.C., the US (Fishman et al., 2014)	Shared bike	Walking Public transport	
Minnesota, the US (Fishman et al., 2014)	Shared bike	Walking (Private) Car	
Asia-Pacific			
Seoul, South Korea, (Kim, 2023)	Shared bike		Public transport (metro)
Beijing, China (Fan & Zheng, 2020)	Shared bike		Public transport (metro)
Beijing, China (Campbell et al., 2016)	Shared bike	Walking Private bike Private e-bike	
	Shared e-bike	Walking Private bike Private e-bike Public transport (bus)	
Melbourne and Brisbane, Australia (Fishman et al., 2014)	Shared bike	Walking Public transport (Private) Car	

complement SMM with public transport (Huang et al., 2024; Ma et al., 2022; van Kuijk et al., 2022; Yan et al., 2019). Studies also found that people who have better access to cars tend to replace their car trips with SMM (Fukushige et al., 2021; Guo & Zhang, 2021), and people who have no access to a car tend to use SMM to complement transit trips (Yan et al., 2023). A few studies found that people who live in areas with lower transit coverage within a city tend to use shared e-scooters as alternatives to public transport (Luo et al., 2021; Weschke et al., 2022).

Hence, it can be concluded that the substitution and complementarity relationships between SMM modes and existing transport modes vary in different urban settings and mobility systems. In cities that are more car-centric with low density, about 10–20 % of private car trips and 20–40 % of taxi/ride-hailing trips are likely to be substituted by SMM modes (Wang et al., 2023). In more compact and active mode-oriented cities, private bikes with a percentage varying from 10 % to 50 % are likely to be substituted by SMM modes. More generally, walking is substituted by various SMM modes, and public transport is substituted by electric-powered SMM modes. Moreover, the substitution and complementarity relationships between SMM and public transport usually coexist. Also, the current literature suggests that the interactions between SMM and existing transport modes vary in traveller groups with different characteristics and living in different areas within a city, which implies that the role of SMM in multimodality may also differ.

3. Data and methods

3.1. Study areas

We used three European cities as case study areas: Utrecht (the Netherlands), Greater Manchester (the United Kingdom) and Malmö (Sweden). These three cities have different urban settings and mobility systems (Table 2).

Utrecht is the fourth largest city in the Netherlands, with the highest population density among the three study areas. Located in the heart of the Netherlands, Utrecht is well-connected to major cities and the rest of the country by both the highway and railway networks. Utrecht has a local public transport system with bus and tram. Utrecht has an extensive network of bike paths and more than half (52.9 %) of the roads in the city have a speed limit of 30 km/h or less. It is highly cycling-oriented, with cycling accounting for half of the overall travel. Four forms of SMM are available in Utrecht in the survey year. Shared bikes (public transport rental bikes, *OV-fiets*) have been offered since 2000. Shared e-bikes, shared e-mopeds and shared e-cargo bikes became available in early 2021.

Table 2
Characteristics of case study areas.

	Utrecht, the Netherlands	Greater Manchester, the UK	Malmö, Sweden
Population	359,370	2,867,800	351,749
Area	99.21 km^2	1276 km^2	156.95 km^2
Population density	3830/km^2	2247/km^2	2241/km^2
Passenger car per household	0.7	1.1	0.7
Length of bike paths			
–Total	420 km	800 km	515 km
–Per km^2	4.23 km/km^2	0.63 km/km^2	3.28 km/km^2
Percentage of road length with a minimum speed limit[a]	52.9 % (≤30 km/h)	41.9 % (≤32 km/h)	6.0 % (≤30 km/h) 69.0 % (≤40 km/h)
Transit system	• Bus • Tram • Train	• Bus • Tram (Metrolink) • Train	• Bus • Train
Modal share			
–Private car	18 %	56 %	34 %
–Public transport	6 %	10 %	25 %
–Cycling	49 %	2 %	26 %
–Walking	27 %	29 %	14 %
–Other	1 %	3 %	1 %
Shared micromobility modes (approximate average cost)[b]	• Shared bike (€4.45/day) • Shared e-bike (€0.25/min) • Shared e-moped (€0.30/min) • Shared e-cargo bike (€0.30/min)	• Shared bike (£0.05/min) • Shared e-bike (£0.10/min) • Shared e-scooter (£0.17/min)	• Shared bike (€1.70/h) • Shared e-scooter (€0.22/min)

Note. The data for Utrecht are from CBS, 2021 (https://opendata.cbs.nl/statline/#/CBS/nl/dataset/85039NED/table?ts=1703859206522) and ODiN, 2021 (https://www.cbs.nl/-/media/_excel/2021/12/modalsplit2019–gemeente-utrecht-februari2021.xlsx). The data for Greater Manchester are from Census, 2021 (https://www.ons.gov.uk/visualisations/customprofiles/build/#E47000001) and GM TRADS, 2019–2021 (https://tfgm.com/trads). The data for Malmö are from SCB, 2021 (https://www.statistikdatabasen.scb.se/pxweb/en/ssd/) and RVU Sweden, 2018 (https://malmo.se/Facts-and-statistics/Travel-habits-of-residents.html).

[a] Due to the different road regulations of the three countries, we chose different minimum speed limits for the three cities. The minimum speed limit for Utrecht is 30 km/h, for Greater Manchester is 20mph (around 32 km/h), and for Malmö we chose both 30 km/h and 40 km/h as minimum speed limits because there are very few roads in Malmö with a speed limit of 30 km/h as 40 km/h is the default speed limit in built-up areas in Sweden.

[b] £1 is approximately €1.2, and the average cost of shared micromobility in Malmö has been converted from Swedish Kronor to Euros.

Greater Manchester is a city region in North West England, comprising 10 boroughs. Greater Manchester is much larger in population and area than the other two study areas. Greater Manchester has a local public transport system with bus and tram (Metrolink). It is more car-dependent than the other two study areas, with more passenger cars per household and a higher modal share of car use. While Greater Manchester has been expanding its network of bike paths over the past years, the coverage of bike paths in the city is still much lower than Utrecht and Malmö. Around 40 % of roads there have a speed limit of 20mph (32 km/h) or less. SMM services are not widespread in Greater Manchester. In the survey year, shared bikes, shared e-bikes, and shared e-scooters were available in parts of the city region. Shared e-scooters

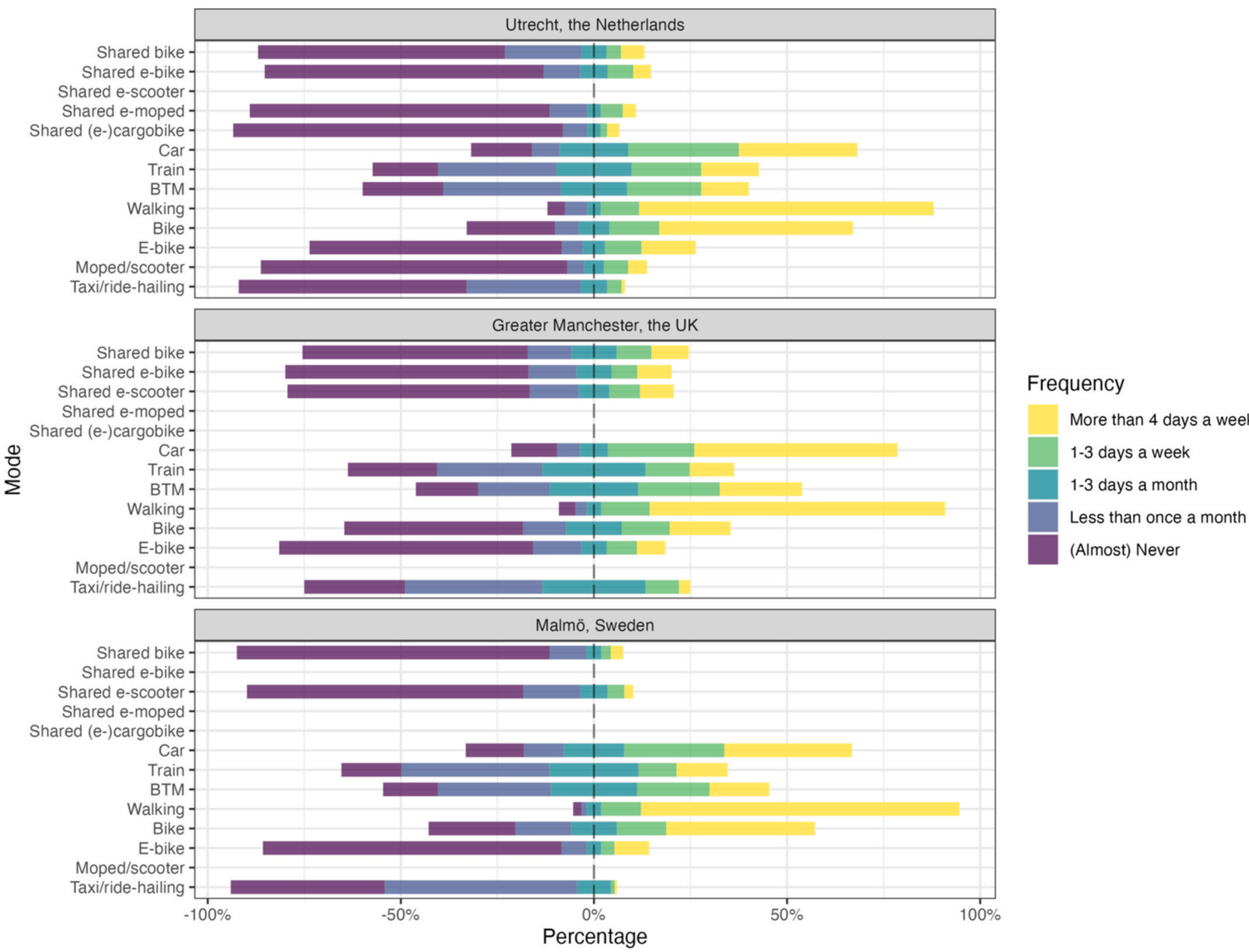

Fig. 1. Frequency of mode use.

Table 3
Summary statistics of selected variables.

	NL	UK	SE
Sample size	349	540	1014
Personal demographic factors			
Gender			
Man	43.55 %	44.07 %	42.90 %
Woman	55.01 %	55.19 %	56.71 %
Non-binary	0.57 %	0.37 %	0.30 %
Prefer not to say	0.86 %	0.37 %	0.10 %
Age			
18–29	22.06 %	36.48 %	18.15 %
30–39	27.79 %	30.74 %	28.01 %
40–49	12.61 %	16.11 %	15.29 %
50–59	16.91 %	10.19 %	15.29 %
60+	17.77 %	6.48 %	23.08 %
Prefer not to say	2.87 %	0.00 %	0.20 %
Household income			
Very high	12.03 %	15.74 %	24.75 %
High	18.05 %	17.04 %	20.32 %
Medium	17.48 %	18.89 %	21.20 %
Low	19.20 %	19.44 %	10.45 %
Very low	16.91 %	18.89 %	6.31 %
Prefer not to say	16.33 %	10.00 %	16.96 %
Education level			
High	25.21 %	15.19 %	18.24 %
Medium	33.24 %	34.26 %	34.81 %
Low	38.68 %	46.11 %	41.22 %
Other or prefer not to say	2.87 %	4.44 %	5.72 %
Presence of children in the household			
Yes	26.93 %	42.22 %	28.80 %
No	73.07 %	57.78 %	71.20 %
Employment status			
Full-time	46.13 %	62.41 %	58.58 %
Part-time (self-employed)	26.93 %	11.48 %	7.10 %
Student	5.44 %	7.96 %	9.17 %
Retired	6.59 %	3.33 %	16.27 %
Unemployed	14.90 %	14.81 %	8.88 %
Personal travel factors			
Driver's license			
Yes	83.67 %	74.26 %	85.60 %
No	15.47 %	25.74 %	14.40 %
Car ownership			
Personal car	33.24 %	48.52 %	34.22 %
Household car	48.14 %	25.74 %	43.20 %
No car	18.62 %	25.74 %	22.58 %
Bike ownership			
Yes	70.77 %	35.74 %	79.29 %
No	29.23 %	64.26 %	20.71 %
PT season ticket subscription			
Yes	59.31 %	31.67 %	36.88 %
No	40.69 %	68.33 %	63.12 %
Weekday travelling hours			
Less than 0.5 h	22.35 %	19.26 %	29.29 %
0.5–1 h	33.81 %	33.89 %	36.19 %
1–1.5 h	18.62 %	27.22 %	16.47 %
1.5–2 h	13.75 %	10.74 %	10.16 %
More than 2 h	11.46 %	8.89 %	7.89 %
Weekend travelling hours			
Less than 0.5 h	36.68 %	32.22 %	42.11 %
0.5–1 h	25.21 %	21.85 %	30.57 %
1–1.5 h	17.48 %	12.04 %	13.21 %
1.5–2 h	10.03 %	25.74 %	6.90 %
More than 2 h	10.60 %	8.15 %	7.20 %
Neighbourhood spatial factors (mean)			
Population density (1000/km^2)	7.32	4.09	4.27
Distance to the city centre (km)	4.42	6.62	4.01
Distance to the train station (km)	2.02	1.77	1.85
Public transport density (1000/km^2)	8.86	6.28	2.53
Cycling way density (km/km^2)	5.20	1.02	4.71
Walking way density (km/km^2)	10.41	7.63	9.51
Percentage of roads with a speed limit of 30 km/h or less (32 km/h for UK) (%)	62.59	43.17	5.71

could only legally be ridden on public roads and paths if they were part of the trials that existed in a few boroughs. Therefore, our study focused on areas where SMM operated, covering Manchester City, Salford, and the adjacent Trafford.

Malmö is the third largest city in Sweden, with a similar population as Utrecht but closer population density to Greater Manchester. It is located at the southern tip of Sweden and across the Sound (Öresund) from Copenhagen, Denmark, so it connects not only numerous local cities but also some neighbouring countries by railway. Malmö has a well-developed network of bike paths, but very few roads there have a speed limit of 30 km/h or less as the default speed limit is 40 km/h in its built-up areas. The local public transport system of Malmö only has buses, but Malmö is the most transit-oriented city among the three study areas. Shared bikes and shared e-scooters were two forms of SMM offered in Malmö in the survey year. The Malmö station-based bike-sharing system started to be operated in 2016, and dockless shared bikes became available later. Shared e-scooters started to be offered by private operators in 2019.

In the text below, we use the abbreviations NL, UK and SE when describing the three case study areas.

3.2. Data

Data was collected through an online survey conducted in all three cities from July to September 2022. The data collection was part of a project aiming to gain knowledge about the implications of SMM for travel behaviour, sustainability, and inclusion, as well as how SMM are best combined with existing transport systems and public space. The cross-sectional design required a sample including both SMM users and non-users for comparison to investigate the implications of SMM. Survey participants were randomly recruited from residents aged over 18 in the areas where SMM services were available via local survey companies (Guan et al., 2024). Each respondent was asked questions about attitudes towards and usage of SMM, travel behaviour, travel experience, social inclusion, and subjective well-being. The survey received 2921 responses in total, and after the data cleaning process, the sample size for the current analysis is 1903 (349 NL cases, 540 UK cases, and 1014 SE cases).

For the current study, we used respondents' self-reported frequency of using SMM modes and existing transport modes to measure their travel patterns. To better understand the role of SMM in multimodal travel, we included both SMM users and non-users to compare their travel patterns. Fig. 1 shows the distribution of respondents' frequency of using available transport modes in each study area.

We used respondents' self-reported personal demographic factors and personal travel factors (see Table 3) as personal-level variables to explain which traveller groups would be more likely to present specific travel patterns. In addition, we linked individuals' residential addresses to publicly available data from multiple sources as neighbourhood-level variables to explain where users of specific travel patterns are more likely to live within the city. NL data were linked at PC-4 (4-digit postal code) level, with an average area of approximately 6.73 km^2. UK and SE data were linked at PC-3 (3-digit postal code) level, with average areas of approximately 20.57 km^2 and 18.14 km^2 respectively. *Population density*, *distance to the city centre* and *distance to the train station* were from census and geospatial statistics of each country or city authority. We used the schedule of buses and trams from GTFS data (recorded from January 2022 to June 2022) to calculate the number of bus and tram lines passing through all bus stops and tram stations in a spatial unit (PC-4 or PC-3) per day and divided the total number by the area of the spatial unit as the variable *public transport frequency density*. We used the cycling road and walking road layers from OpenStreetMap to calculate the average length of cycling way and walking way per square kilometre in each spatial unit, defining these as the variables *cycling way density* and *walking way density*. *Cycling way density* served as an indicator of the sufficiency of cycling facilities (including cycle paths that are drawn as its own way and cycle lanes that are tagged on the main roadway) within an individual's residential neighbourhood. Additionally, based on the attribute field "maximum speed" of the roads layer from OpenStreetMap, which specifies the maximum legal speed limit on each road, we calculated the proportion of the length of roads with a speed limit of 30 km/h or less relative to the total length of roads within each postal code area (for the UK sample, the speed limit was 20 mph, approximately 32 km/h). *Percentage of roads with a speed limit of 30 km/h or less* was used to evaluate the road environment for the use of micromobility, particularly from the safety perspective.

3.3. Identification of travel patterns: Latent Class Analysis

Latent Class Analysis (LCA) was used to identify travel patterns of modal combinations. LCA is a statistical procedure identifying several classes within a latent variable measured by a set of observed indicators (Bakk & Kuha, 2018; Goodman, 1974; McCutcheon, 1987). Concretely, this model-based clustering method uses a categorical latent variable to explain all associations (i.e. common variances) among a set of observed indicators through a statistical process. Therefore, by using mode use frequency as indicators, LCA can identify latent classes that exhibit the patterns of interactions between the use of different travel modes, thus answering our first research question. In identifying clusters, a major advantage of LCA over conventional clustering techniques like k-means is that LCA provides several statistical tests to assess model fit, so we can use formal criteria to compare the performance of models with different numbers of classes and decide the optimal number, which is more flexible and rigorous. LCA also has its strengths when being extended to compare group attributes and analyse the predictors of class membership. LCA assigns individuals to all latent classes based on probabilities calculated from the estimated parameters and the individual's response to the set of indicators, rather than restricting each individual to a single cluster. Thus, accounting for the weights of individuals in each class and classification errors when relating latent classes to external variables can reduce bias (Asparouhov & Muthén, 2014). In this study, we minimise the bias in comparing characteristics across identified travel patterns by taking into account the weights and classification errors.

Respondents' self-reported frequency of using SMM modes and existing transport modes were used as observed indicators. Different sets of transport modes were selected for each study area according to the availability (see Fig. 1), and separate models were applied to each city. Respondents were asked to answer their frequency of using transport modes based on a seven-point scale from 1 '(Almost) never' to 7 '(Almost) daily', and we merged it into five categories, namely "More than 4 days a week", "1-3 days a week", "1-3 days a month", "Less than once a month" and "(Almost) never". We used them as categorical variables in the analysis.

Consider the vector of indicators $Y_i = (Y_{i1}, Y_{i2}, \dots, Y_{ik})$, where Y_{ik} denotes individual i's frequency of using transport mode k. LCA assumes there is a categorical latent variable X that explains associations between indicators, and individual i has a certain probability of belonging to each of the T latent classes depending on Y_i. The LCA model can then be written as:

$$p(Y_i) = \sum_{t=1}^{T} p(X=t) p(Y_i | X=t) \tag{1}$$

where $p(X=t)$ is the (unconditional) probability that an individual belongs to latent class t, and $p(Y_i|X=t)$ is the class-specific probability of an individual's responses to the indicators given the latent class t. Making the 'local independence' assumption that the K observed indicators are independent within the latent classes, leading to:

$$p(Y_i) = \sum_{t=1}^{T} p(X=t) \prod_{k=1}^{K} p(Y_{ik} | X=t) \tag{2}$$

Maximum likelihood (ML) estimation was used for estimating all the parameters (Bakk & Kuha, 2018; Dayton & Macready, 1988), i.e. maximising the following function:

$$ln\mathscr{L} = \sum_{i=1}^{I} lnP(Y_i) \tag{3}$$

where I is the total number of individuals within the sample. The number of classes T is determined by comparing the goodness-of-fit of models with different values of T using a series of criteria including log-likelihood, Akaike information criterion, Bayesian information criterion, and entropy (values closer to 1 indicate better separation between classes) (Bakk & Kuha, 2021; Magidson, 1981; Vermunt, 2010).

The posterior probability of each individual belonging to each class was then calculated based on the estimated parameters, and everyone was assigned to the class with the highest posterior probability.

3.4. Comparison of user characteristics across travel patterns

Based on the identification of individuals' travel patterns, we then compared the personal characteristics and residential neighbourhood spatial characteristics of different traveller groups (individuals with the same travel pattern). Descriptive analyses of characteristics of each traveller group combined with independence tests were used for the comparisons: Chi-square tests were used to compare the distribution of personal characteristics including demographic factors and travel factors since all these variables were categorical; One-way ANOVA tests were used to compare the means of neighbourhood spatial factors as all these variables were continuous.

3.5. Methodological limitations and post-hoc analysis

We used descriptive analysis combined with independence tests to compare user characteristics of travel patterns. We used this method for the main analysis because it could be concise and straightforward to show the class differences and manifest the features of each travel pattern. However, there are certain limitations with the methods: 1) the analysis only indicated whether the distribution or means of variables significantly differ across all classes, but not the specific classes from which each class differs; 2) the analysis did not take classification errors into account, which may lead to biased results.

To minimise the impact of the methodological limitations on the research results, we did a post-hoc analysis to estimate the associations between user characteristics and travel patterns by performing multinomial logistics regression models based on the clustering results of LCA. Such an extension of LCA is called the three-step approach, and we used the ML bias-adjusted method to account for classification errors in the analysis (Asparouhov & Muthén, 2014; Vermunt, 2010). The first step is a basic LCA with only the latent class indicators, to decide the optimal number of classes and estimate all the parameters denoting the association between latent classes and indicators, which is exactly what was done in 3.3 Identification of travel patterns: Latent Class Analysis. In the second step, individuals were assigned to the class in which they had the highest posterior probability, and a classification uncertainty rate was calculated as the probability of individuals belonging to other classes but being assigned to the most likely class. In the third step, we fitted a multinomial logistic regression model to regress the most likely class on the personal characteristics and neighbourhood spatial characteristics, adjusting for the classification uncertainty rate to account for misclassifications. We did the analyses and imputed the missing data using multiple imputations in Mplus 8.9. The results of the post-hoc analysis are presented in Appendix A. We used the results of the post-hoc analysis to cross-validate that of the main analysis in the discussion.

Table 4
Goodness-of-fit indices for models with different class numbers.

	Model	Npar	LL	AIC	BIC	SA-BIC	Entropy
NL	1-class	48	−4608.75	9313.49	9498.53	9346.26	1.00
	2-class	97	−4240.87	8675.75	9049.69	8741.97	0.96
	3-class	146	−4044.05	8380.11	8942.95	8479.79	0.91
	4-class	195	−3959.32	8308.65	9060.38	8441.78	0.93
	5-class	244	−3896.48	8280.97	9221.60	8447.55	0.94
	6-class	293	−3838.39	8262.78	9392.32	8462.82	0.94
	7-class	342	−3790.50	8265.00	9583.43	8498.49	0.93
UK	1-class	40	−6893.33	13,866.66	14,038.32	13,911.35	1.00
	2-class	81	−6215.23	12,592.46	12,940.07	12,682.95	0.93
	3-class	122	−6039.89	12,323.79	12,847.36	12,460.09	0.92
	4-class	163	−5904.09	12,134.17	12,833.70	12,316.28	0.89
	5-class	204	−5831.68	12,071.37	12,946.85	12,299.28	0.89
	6-class	245	−5768.35	12,026.70	13,078.13	12,300.41	0.90
	7-class	286	−5717.18	12,006.36	13,233.75	12,325.88	0.90
SE	1-class	36	−10,376.19	20,824.37	21,001.55	20,887.21	1.00
	2-class	73	−10,036.94	20,219.88	20,579.16	20,347.30	0.73
	3-class	110	−9874.19	19,968.38	20,509.76	20,160.39	0.74
	4-class	147	−9760.42	19,814.84	20,538.32	20,071.44	0.80
	5-class	184	−9648.40	19,664.79	20,570.37	19,985.98	0.81
	6-class	221	−9566.49	19,574.99	20,662.67	19,960.76	0.82
	7-class	258	−9498.46	19,512.92	20,782.71	19,963.28	0.82

Npar = Number of parameters.
LL = Log-Likelihood.
AIC = Akaike Information Criteria.
BIC = Bayesian Information Criteria.
SA-BIC = Sample-size adjusted Bayesian Information Criteria.

4. Results

4.1. Identified travel patterns

Table 4 provides the goodness-of-fit results of LCA models with 1–7 latent classes. The goal of comparison is to find the most parsimonious model that adequately explains distinct latent characteristics with the smallest number of classes: low AIC, BIC and SA-BIC, high log-likelihood and entropy, and a small number of classes. Also, to better interpret and compare between cities, if possible, determine the same number of classes for all cities. Therefore, parsimony and interpretability supported the selection of the 4-class model for all cities.

Fig. 2 presents the within-class distribution of indicators. The travel patterns of each city were defined as follows. In the following discussion, “frequently” refers to a frequency of at least once a week, and “occasionally” refers to a frequency of at least once a month.

NL class 1 (9 % of the NL sample): *SMM-frequently multimodal* (*F-MM*). All people in this class use shared bikes and shared e-bikes, mostly at least once a week (77 %). Most people in this class also use shared e-mopeds and shared e-cargo bikes frequently (46 % at least once a week). People in this class use all the existing transport modes frequently.

NL class 2 (11 %): *SMM-occasionally active multimodal* (*O-AM*). Most people in this class use at least one SMM mode (86 %). Shared e-bikes are used more frequently than other SMM modes, followed by shared bikes. Most people in this class use shared e-bikes and/or shared bikes at least once a month (55 %), and only a few people use shared e-mopeds or shared e-cargo bikes (5 %). Most people in this class also use their private bikes at least once a month (73 %). They also use trains, BTM and cars, and use trains more frequently than BTM and cars.

NL class 3 (36 %): *SMM-less active/PT* (*N-AP*). Among the four modes of SMM, except for shared bikes, which are occasionally used by very few people in this class (6 % at least once a month), the other three SMM modes are rarely used. Almost all people in this class use private bikes more than four days a week (72 %), and most of them use trains and/or BTM (refers to local public transport modes, which usually include bus, tram, and metro) at least once a week (namely 61 % and 51 %). People in this class use cars less frequently than public transport.

NL class 4 (44 %): *SMM-less car dominant* (*N-C*). Almost no people in this class use any of the SMM modes (5 % ever used). They use cars frequently, and most of them use cars at least once a week (72 %). They also use their private bikes, although at a lower frequency than car use.

UK class 1 (12 % of the UK sample): *SMM-frequently multimodal* (*F-MM*). People in this class use all three SMM modes frequently, mostly at least once a week (87 %). They also use all the existing transport modes frequently, including their private bikes and e-bikes.

UK class 2 (27 %): *SMM-occasionally car multimodal* (*O-CM*). People in this class use all SMM modes occasionally, but they use shared bikes more frequently than shared e-bikes and shared e-scooters. Most of them frequently use cars (81 %) and occasionally use trains (69 %) and BTM (78 %). They also occasionally use their private bikes and e-bikes.

UK class 3 (35 %): *SMM-less car/PT* (*N-CP*). Almost no people in this class use SMM (4 % at least once a month). Although they use cars regularly, their frequency of using cars is lower than the other three UK classes. People in this class also occasionally use trains and BTM.

UK class 4 (26 %): *SMM-less car dominant* (*N-C*). Almost no people in this class use SMM (4 % at least once a month). They exclusively use cars and hardly use other transport modes (except walking).

SE class 1 (5 % of the SE sample): *SMM-frequently multimodal* (*F-MM*). Similar to NL class 1 and UK class 1, people in SE class 1 also use all SMM modes and existing transport modes frequently.

SE class 2 (47 %): *SMM-less active/car* (*N-AC*). People in this class hardly use SMM modes, but they use their private bikes frequently. They also frequently use cars.

SE class 3 (30 %): *SMM-less PT multimodal* (*N-PM*). Except for very few people who frequently use shared bikes (5 %), most people in this class hardly use any SMM mode. Most people in this class use trains and BTM at least once a week (namely 61 % and 81 %). They also frequently use private bikes.

SE class 4 (17 %): *SMM-less car dominant* (*N-C*). Few people in this class use SMM (8 % at least once a week). Most of them frequently use cars (77 %) and some of them also use private bikes frequently (32 %).

4.2. User characteristics of different travel patterns

4.2.1. Personal demographic characteristics

Table 5 presents the comparison of user characteristics between travel patterns. For the NL sample, all personal demographic factors except household income differ significantly between classes. Men and

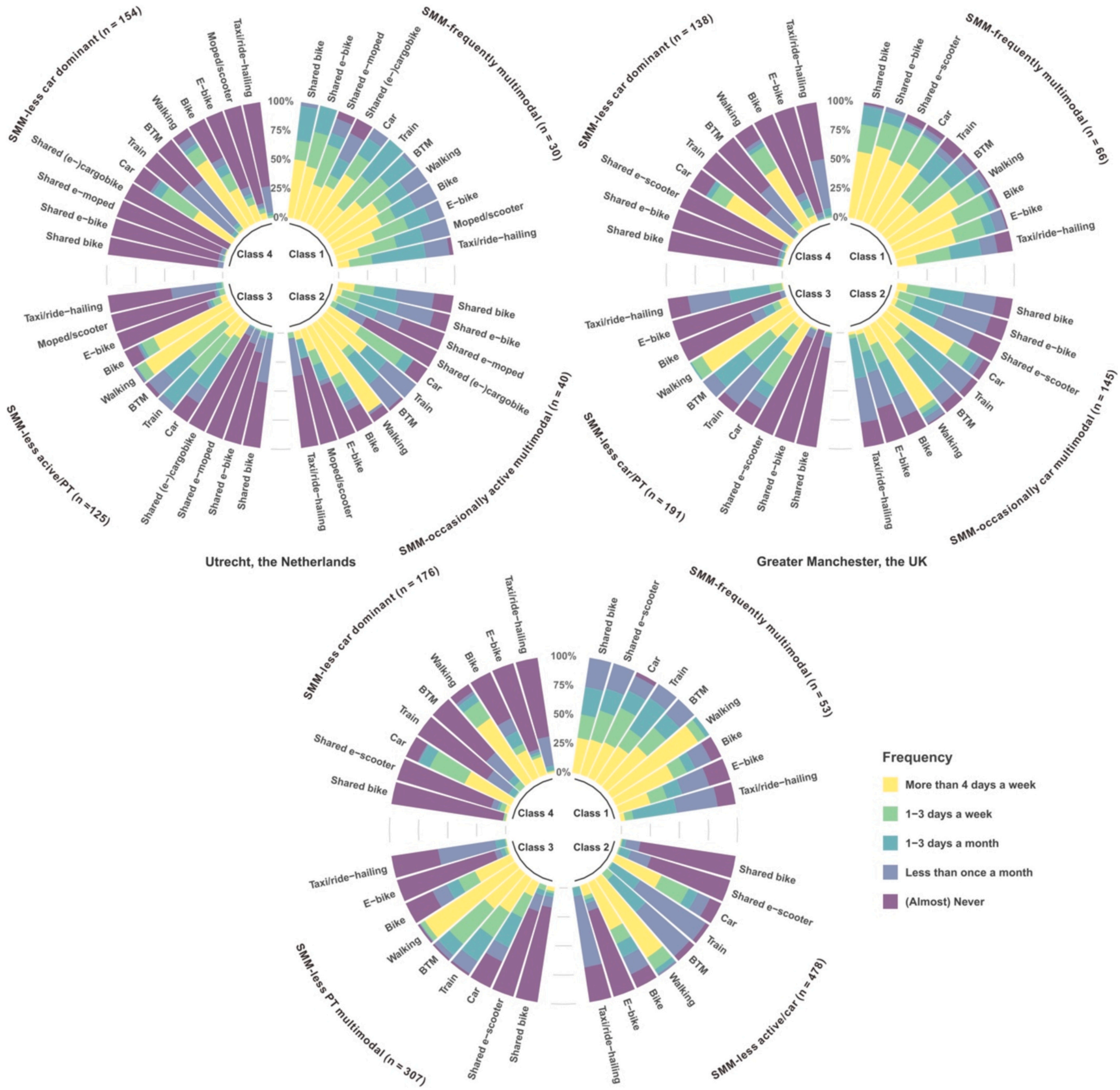

Fig. 2. Distribution of the modes use frequency within each class.

Table 5
Comparisons of user characteristics of different travel patterns within each city.[a]

Personal demographic factors	NL					UK					SE				
	Class 1	*Class 2*	*Class 3*	*Class 4*	χ^2	*Class 1*	*Class 2*	*Class 3*	*Class 4*	χ^2	*Class 1*	*Class 2*	*Class 3*	*Class 4*	χ^2
	F-MM	*O-AM*	*N-AP*	*N-C*		*F-MM*	*O-CM*	*N-CP*	*N-C*		*F-MM*	*N-AC*	*N-PM*	*N-C*	
Gender					21.41**					22.54***					15.87*
Man	**56.67 %**	**55.00 %**	41.60 %	39.61 %		**63.64 %**	**52.41 %**	35.60 %	37.68 %		43.40 %	45.40 %	35.83 %	48.30 %	
Woman	43.33 %	40.00 %	**56.80 %**	**59.74 %**		36.36 %	47.59 %	**62.83 %**	**61.59 %**		**56.60 %**	**54.39 %**	**63.19 %**	**51.70 %**	
Non-binary	0.00 %	5.00 %	0.00 %	0.00 %		0.00 %	0.00 %	0.52 %	0.72 %		0.00 %	0.00 %	0.98 %	0.00 %	
Age					85.26***					96.60***					77.50***
18–29	43.33 %	**45.00 %**	28.00 %	7.14 %		**48.48 %**	**46.90 %**	**41.88 %**	12.32 %		28.30 %	15.69 %	26.38 %	7.39 %	
30–39	**46.67 %**	30.00 %	**32.00 %**	20.13 %		34.85 %	35.86 %	23.04 %	**34.06 %**		**43.40 %**	**28.24 %**	**29.64 %**	19.89 %	
40–49	10.00 %	12.50 %	12.80 %	12.99 %		12.12 %	14.48 %	17.80 %	17.39 %		9.43 %	16.53 %	15.64 %	13.07 %	
50–59	0.00 %	5.00 %	11.20 %	27.92 %		3.03 %	2.07 %	8.38 %	24.64 %		7.55 %	15.90 %	12.70 %	20.45 %	
60+	0.00 %	7.50 %	16.00 %	**31.82 %**		1.52 %	0.69 %	8.90 %	11.59 %		11.32 %	23.64 %	15.64 %	**39.20 %**	
Household income					19.67					26.36**					31.59**
Very high	23.33 %	7.50 %	13.60 %	9.74 %		**24.24 %**	13.10 %	14.66 %	15.94 %		22.64 %	**28.45 %**	**21.17 %**	**21.59 %**	
High	23.33 %	35.00 %	16.80 %	13.64 %		**24.24 %**	**24.83 %**	11.52 %	13.04 %		**26.42 %**	21.55 %	20.20 %	15.34 %	
Medium	26.67 %	22.50 %	17.60 %	14.29 %		21.21 %	22.07 %	18.85 %	14.49 %		**26.42 %**	21.13 %	20.20 %	**21.59 %**	
Low	6.67 %	15.00 %	24.80 %	18.18 %		18.18 %	22.76 %	19.37 %	16.67 %		7.55 %	7.74 %	13.36 %	13.64 %	
Very low	10.00 %	12.50 %	16.80 %	19.48 %		10.61 %	12.41 %	**23.04 %**	**23.91 %**		3.77 %	4.39 %	11.07 %	3.98 %	
Education level					31.68***					15.02					34.45***
High education	23.33 %	27.50 %	33.60 %	18.18 %		24.24 %	15.86 %	11.52 %	15.22 %		22.64 %	15.69 %	23.78 %	14.20 %	
Medium education	33.33 %	**37.50 %**	**40.00 %**	26.62 %		36.36 %	40.69 %	34.55 %	26.09 %		**39.62 %**	**40.59 %**	32.25 %	22.16 %	
Low education	36.67 %	30.00 %	24.00 %	**53.25 %**		37.88 %	42.07 %	47.12 %	52.90 %		33.96 %	38.28 %	**39.09 %**	**55.11 %**	
Living with children	**60.00 %**	30.00 %	19.20 %	25.97 %	20.73***	**51.52 %**	45.52 %	32.98 %	47.10 %	11.01*	39.62 %	30.96 %	24.76 %	26.70 %	6.94
Employment status					57.39***					46.12***					65.35***
Full-time	**73.33 %**	**70.00 %**	**47.20 %**	**33.77 %**		**75.76 %**	**73.10 %**	**50.79 %**	**60.87 %**		**69.81 %**	**61.92 %**	55.05 %	52.27 %	
Part-time (self-employed)	6.67 %	22.50 %	28.00 %	31.17 %		7.58 %	11.72 %	10.99 %	13.77 %		7.55 %	6.69 %	7.17 %	7.95 %	
Student	3.33 %	5.00 %	11.20 %	1.30 %		7.58 %	8.28 %	12.04 %	2.17 %		9.43 %	6.49 %	**16.61 %**	3.41 %	
Retired	0.00 %	0.00 %	4.00 %	11.69 %		0.00 %	1.38 %	3.66 %	6.52 %		3.77 %	16.95 %	10.10 %	**28.98 %**	
Unemployed	16.67 %	2.50 %	9.60 %	22.08 %		9.09 %	5.52 %	22.51 %	16.67 %		9.43 %	7.95 %	11.07 %	7.39 %	

Personal travel factors	NL					UK					SE				
	Class 1	*Class 2*	*Class 3*	*Class 4*	χ^2	*Class 1*	*Class 2*	*Class 3*	*Class 4*	χ^2	*Class 1*	*Class 2*	*Class 3*	*Class 4*	χ^2
	F-MM	*O-AM*	*N-AP*	*N-C*		*F-MM*	*O-CM*	*N-CP*	*N-C*		*F-MM*	*N-AC*	*N-PM*	*N-C*	
Having a driver's license	96.67 %	85.00 %	78.40 %	85.06 %	5.70	**87.88 %**	**86.21 %**	**55.50 %**	**81.16 %**	55.84***	**86.79 %**	**90.59 %**	**72.64 %**	**94.32 %**	62.40***
Car ownership					19.76**					84.95***					115.32***
Personal car	**60.00 %**	40.00 %	11.20 %	**44.16 %**		**66.67 %**	**53.10 %**	27.75 %	**63.77 %**		33.96 %	38.91 %	18.24 %	**49.43 %**	
Household car	36.67 %	**50.00 %**	**65.60 %**	35.71 %		22.73 %	35.17 %	27.75 %	14.49 %		**47.17 %**	**44.77 %**	40.07 %	43.18 %	
No car	3.33 %	10.00 %	23.20 %	20.13 %		10.61 %	11.72 %	**44.50 %**	21.74 %		18.87 %	16.32 %	**41.69 %**	7.39 %	
Having a private bike	46.67 %	**75.00 %**	**82.40 %**	**64.94 %**	19.48***	**54.55 %**	49.66 %	27.23 %	23.91 %	36.82***	**77.36 %**	**85.15 %**	**75.90 %**	**69.89 %**	21.74***
PT season ticket subscription	**86.67 %**	**72.50 %**	**84.00 %**	30.52 %	96.66***	**57.58 %**	48.28 %	28.27 %	6.52 %	80.30***	**71.70 %**	15.90 %	**77.85 %**	11.93 %	386.40***
Weekday travelling hours					30.31**					54.02***					75.33***
Less than 0.5 h	3.33 %	10.00 %	20.00 %	31.17 %		12.12 %	6.21 %	23.04 %	31.16 %		11.32 %	29.08 %	27.04 %	**39.20 %**	
0.5–1 h	**40.00 %**	**37.50 %**	**28.80 %**	**35.71 %**		21.21 %	34.48 %	**39.27 %**	**31.88 %**		22.64 %	**43.10 %**	**28.34 %**	35.23 %	
1–1.5 h	36.67 %	22.50 %	16.80 %	15.58 %		**37.88 %**	**37.93 %**	21.47 %	18.84 %		**43.40 %**	13.81 %	18.89 %	11.36 %	
1.5–2 h	13.33 %	15.00 %	18.40 %	9.74 %		18.18 %	13.79 %	6.81 %	9.42 %		9.43 %	7.53 %	15.96 %	7.39 %	
More than 2 h	6.67 %	15.00 %	16.00 %	7.79 %		10.61 %	7.59 %	9.42 %	8.70 %		13.21 %	6.49 %	9.77 %	6.82 %	
Weekend travelling hours					28.08**					31.14**					20.69
Less than 0.5 h	16.67 %	**32.50 %**	**32.80 %**	**44.81 %**		21.21 %	31.03 %	**36.65 %**	32.61 %		26.42 %	39.96 %	45.93 %	46.02 %	
0.5–1 h	26.67 %	20.00 %	26.40 %	25.32 %		**24.24 %**	**31.72 %**	17.80 %	15.94 %		39.62 %	29.92 %	28.01 %	34.09 %	
1–1.5 h	**33.33 %**	25.00 %	12.00 %	16.88 %		16.67 %	11.03 %	11.52 %	11.59 %		20.75 %	14.85 %	13.03 %	6.82 %	

(*continued on next page*)

Table 5 (*continued*)

Personal travel factors	NL Class 1 F-MM	NL Class 2 O-AM	NL Class 3 N-AP	NL Class 4 N-C	NL χ^2	UK Class 1 F-MM	UK Class 2 O-CM	UK Class 3 N-CP	UK Class 4 N-C	UK χ^2	SE Class 1 F-MM	SE Class 2 N-AC	SE Class 3 N-PM	SE Class 4 N-C	SE χ^2
1.5–2 h	16.67 %	5.00 %	14.40 %	6.49 %		**24.24 %**	17.93 %	24.61 %	**36.23 %**		5.66 %	8.37 %	6.19 %	4.55 %	
More than 2 h	6.67 %	17.50 %	14.40 %	6.49 %		13.64 %	8.28 %	9.42 %	3.62 %		7.55 %	6.90 %	6.84 %	8.52 %	

Neighbourhood spatial factors (Mean)	NL Class 1 F-MM	NL Class 2 O-AM	NL Class 3 N-AP	NL Class 4 N-C	NL F	UK Class 1 F-MM	UK Class 2 O-CM	UK Class 3 N-CP	UK Class 4 N-C	UK F	SE Class 1 F-MM	SE Class 2 N-AC	SE Class 3 N-PM	SE Class 4 N-C	SE F
Population density (1000/km^2)	6.74	7.04	7.43	7.42	0.37	4.02	4.35	4.12	3.79	1.75	4.25	4.11	4.63	4.07	1.90
Distance to the city centre (km)	6.22	4.74	4.20	4.17	2.08	7.63	6.17	6.49	6.84	1.39	3.89	4.18	3.65	**4.22**	4.53**
Distance to the train station (km)	2.64	2.22	1.97	1.89	1.80	1.95	1.76	1.80	1.67	0.90	1.84	1.90	1.72	**1.94**	4.83**
Public transport density (1000/km^2)	8.55	7.98	8.72	9.21	0.31	6.07	7.49	6.36	5.03	2.37	2.50	2.43	2.75	2.42	1.95
Cycling way density (km/km^2)	4.91	5.23	5.18	5.26	0.24	1.11	1.03	1.01	0.99	0.43	4.78	4.63	4.84	4.66	1.20
Walking way density (km/km^2)	9.11	9.93	11.08	10.25	1.83	7.75	9.08	7.03	6.91	2.09	9.62	9.25	10.03	9.25	1.73
Percentage of roads with a speed limit of 30 km/h or less (32 km/h for UK) (%)	59.52	58.00	63.56	63.62	1.36	45.49	46.36	42.67	39.65	1.81	5.67	5.83	5.41	5.92	1.66

[a] If the independence test shows significant difference across classes: for categorical variables, the highest frequency within each cluster is in boldface; for continuous variables, the highest mean value across all clusters is in boldface.

younger people are overrepresented in the two SMM user classes. Compared to the two SMM user classes, higher-educated people are overrepresented in the *SMM-less active/PT* class and lower-educated people are overrepresented in the *SMM-less car dominant* class. People in the *SMM-frequently multimodal* class mostly live with children. In terms of employment status, full-time employed people are overrepresented in the two SMM user classes; students are overrepresented in the *SMM-less active/PT* class; retired or unemployed people are overrepresented in the *SMM-less car dominant* class.

For the UK sample, all personal demographic factors except education level differ significantly between classes. Men and younger people are overrepresented in the two SMM user classes. People under thirty years old are also overrepresented in the *SMM-less car/PT* class, and people over fifty years old are overrepresented in the *SMM-less car dominant* class. Medium- to high-income people are overrepresented in the two SMM user classes. In terms of employment status, full-employed people are overrepresented in the two SMM user classes; students or unemployed people are overrepresented in the *SMM-less car/PT* class; retired or unemployed people are overrepresented in the *SMM-less car dominant* class.

For the SE sample, all personal demographic factors except the presence of children in the household differ significantly between classes. Women are overrepresented in the *SMM-less PT multimodal* class. Younger people are overrepresented in the *SMM-frequently multimodal* and *SMM-less PT multimodal* classes, and older people are overrepresented in the *SMM-less car dominant* class. High-income people are overrepresented in the *SMM-less active/car* class; medium- to high-income people are overrepresented in the *SMM-frequently multimodal* class; and low-income people are overrepresented in the *SMM-less PT multimodal* class. Higher-educated people are overrepresented in the *SMM-frequently multimodal* and *SMM-less PT multimodal* classes, and lower-educated people are overrepresented in the *SMM-less car dominant* class. In terms of employment status, full-time employed people are overrepresented in the *SMM-frequently multimodal* and *SMM-less active/car* classes; students are overrepresented in the *SMM-less PT multimodal* class; retired people are overrepresented in the *SMM-less car dominant* class.

4.2.2. Personal travel characteristics

For the NL sample, all personal travel factors except driver's license ownership differ significantly between classes. Personal car owners are overrepresented in the *SMM-frequently multimodal* class, and people who share cars with other household members are overrepresented in the *SMM-less active/PT* class. Private bike owners are underrepresented in the *SMM-frequently multimodal* class and overrepresented in the *SMM-less active/PT* class. People who subscribe to public transport season tickets are overrepresented in the *SMM-frequently multimodal* and *SMM-less active/PT* classes. Regarding time spent on travelling, compared to other classes, people in the *SMM-occasionally active multimodal* and *SMM-less active/PT* classes travel longer on weekdays; people in the two SMM user classes travel longer on weekends; people in *SMM-less car dominant* class travel shorter on both weekdays and weekends.

For the UK sample, all personal travel factors differ significantly between classes. Driver's license owners are underrepresented in the *SMM-less car/PT* class. Personal car owners are overrepresented in the *SMM-frequently multimodal* and *SMM-less car dominant* classes; people who share cars with other household members are overrepresented in the *SMM-occasionally car multimodal* class; people who do not have a personal or household car are overrepresented in the *SMM-less car/PT* class. Private bike owners and PT season ticket subscribers are both overrepresented in the two SMM user classes. Regarding travelling time, compared to other classes, people in *SMM-frequently multimodal* class travel longer on both weekdays and weekends; people in *SMM-occasionally car multimodal* and *SMM-less car/PT* classes travel shorter on weekends; people in *SMM-less car dominant* class travel shorter on weekdays, but a substantial proportion of them travel longer on

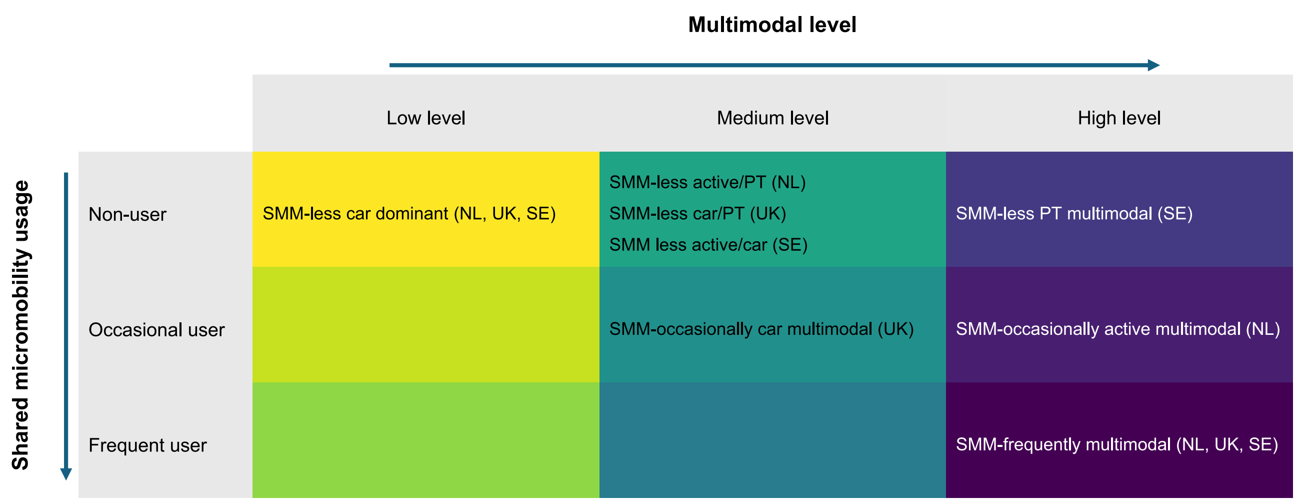

Fig. 3. The multimodal level and SMM usage of travel patterns identified in different cities (Note: Each travel pattern is followed by statements in parentheses indicating in which study areas the travel pattern was identified.)

weekends.

For the SE sample, all personal travel factors except weekend travelling time differ significantly between classes. Driver's license owners are underrepresented in the *SMM-less PT multimodal* class. Personal car owners are overrepresented in the *SMM-less car dominant* class, and people who have no access to cars are overrepresented in the *SMM-less PT multimodal* class. Private bike owners are overrepresented in the *SMM-less active/car* class. People who subscribe to PT season tickets are overrepresented in the *SMM-frequently multimodal* and *SMM-less PT multimodal* classes. Regarding travelling time, people in *SMM-frequently multimodal* and *SMM-less PT multimodal* classes travel longer on weekdays; people in *SMM-less active/car* and *SMM-less car dominant* classes travel shorter on weekdays.

Table 6
A summary of user characteristics of travel patterns with SMM usage.

		Personal demographic characteristics	Personal travel characteristics	Neighbourhood spatial characteristics
NL	F-MM	• Men • Younger • Living with children • Full-time employed	• Having driver's license • Having personal car • No private bike • Having PT season ticket • Travel longer on weekends	
	O-AM	• Men • Younger • Full-time employed	• Travel longer on weekdays • Travel longer on weekends	
UK	F-MM	• Men • Younger • Higher income • Living with children • Full-time employed	• Having personal car • Having private bike • Having PT season ticket • Travel longer on weekdays • Travel longer on weekends	• Higher cycling way density
	O-CM	• Men • Younger • Higher income • Full-time employed	• Having PT season ticket • Travel shorter on weekdays • Travel shorter on weekends	• Higher walking way density
SE	F-MM	• Younger • Higher income • Full-time employed	• Having PT season ticket • Travel longer on weekdays	• Living closer to city centre • Living closer to train station

4.2.3. Neighbourhood spatial characteristics

For the NL sample and UK sample, the neighbourhood spatial factors do not differ significantly between classes. For the SE sample, among the neighbourhood spatial factors, only distance to the city centre and the distance to the train station differ significantly between classes. People in the *SMM-frequently multimodal* and the *SMM-less PT multimodal* classes live closer to the city centre and the train station.

5. Discussion

5.1. In which way is SMM used in conjunction with existing transport modes?

In Fig. 3, we summarised all travel patterns identified in the three study areas and categorised them according to the multimodal level and shared micromobility usage.

In all three study areas, the *SMM-frequently multimodal* class that frequently uses almost all SMM and various existing transport modes was found. Among all identified travel patterns, it is the only one that frequently uses SMM, and it is highly multimodal. This indicates that frequent SMM users typically use multiple SMM modes, and the frequent use of SMM always coincides with the frequent use of diverse existing transport modes in various urban contexts. Therefore, frequent SMM users are extremely multimodal in their daily travel, which is in line with Raux et al.'s (2017) finding that shared bike users are fully multimodal in day-to-day travel and Mohiuddin et al.'s (2024) finding that shared bikes are used at a higher rate by super multimodal travellers. These findings suggest that SMM may be a supplement to existing transport modes to support the daily travel of those who are already highly multimodal.

One occasional SMM user class was found in Utrecht and one in Greater Manchester. The *SMM-occasionally active multimodal* class found in Utrecht is highly multimodal, dominated by active modes. Whereas the *SMM-occasionally car multimodal* class found in Greater Manchester is only moderately multimodal, dominated by car use. Still, there is a commonality between the two SMM occasional user classes, that is those who occasionally use SMM also use private micromobility more frequently than other classes. Occasional SMM users were found to use shared bikes or shared e-bikes more often than other SMM modes, and they also use private bikes or e-bikes as frequently as SMM modes. Previous studies found that SMM may substitute private micromobility

(Ma et al., 2020; Roig-Costa et al., 2024), but as we found occasional SMM users still use their own (e-)bikes frequently, the substitution may be minor. On the contrary, the combined use of SMM and private micromobility indicates that people who use private micromobility frequently may use SMM as a supplement in some circumstances (e.g. private bike owners using a shared e-bike to travel faster when needed, or using a shared bike from a non-home location when a private bike is unavailable), and SMM may have the potential to further increase the modal share of active modes in their daily travel.

Based on randomly selected samples, our study found that most individuals fell into travel patterns that did not use SMM. One non-SMM user class using active modes as the major travel options was found in Utrecht and one in Malmö, namely the *SMM-less active/PT* class of Utrecht and the *SMM-less active/car* class of Malmö. The multimodal level of these two classes, dominated by active modes, is medium. In Malmö, we identified a class of non-SMM users who mainly rely on public transport. This group, called the *SMM-less PT multimodal* class, has a high level of multimodality. These three travel patterns are relatively sustainable with a lower modal share of car use.

In all three study areas, we identified a non-SMM user group that mainly uses cars. This group, called the *SMM-less car dominant* class, has a low level of multimodality. In Utrecht and Malmö, this is the only car dominant travel pattern. While in Greater Manchester, cars dominate all travel patterns, and the difference between travel patterns is mainly in the degree of car dominance and the modal share of public transport, especially trains. Therefore, it can be inferred that trains may have considerable potential to replace car use in Greater Manchester, for certain trips or individuals.

Overall, it can be concluded that SMM users are indeed more multimodal than non-users, which suggest the potential of SMM to support and facilitate multimodal travel.

5.2. How do the user characteristics vary across travel patterns?

Table 6 summarises the user characteristics of travel patterns with SMM usage. Consistent with previous studies on SMM user characteristics, we found that younger people and men are more likely to be in SMM-user classes (Ma et al., 2022; Reck & Axhausen, 2021; Yan et al., 2023). Previous studies found mixed results on the relationship between income and SMM use (Ghaffar et al., 2023; Mohiuddin et al., 2023, 2024; Orvin & Fatmi, 2021), but we found that in our study areas, people in SMM user classes are more likely to have medium to high income. While previous research indicated that SMM users tend to from households without children (Reck & Axhausen, 2021), our study found people who frequently use SMM are likely to live with children. We also found frequent SMM users tend to work full-time. It can be inferred that frequent SMM users take on different social responsibilities, including caregivers and employees, and different responsibilities may require different transport modes to fulfil travel needs. Therefore, SMM may be used as a travel supplement and thereby directly support multimodal travel.

In Utrecht and Greater Manchester, people in SMM user classes are more likely to have a driver's license and/or a personal car, especially for the frequent SMM user class. Although they have better access to cars, they do not exclusively use cars, which indicates that they may deliberately choose different transport modes for different travel needs (Kroesen, 2014; Mao et al., 2016). An interesting finding is that frequent SMM users in Utrecht have lower bike ownership than people who travel in other ways, while frequent SMM users in Greater Manchester have higher bike ownership than people who travel in other ways. These results indicate that in a more cycling-oriented context, SMM may be an alternative option for people who do not have a private bike; while in a less cycling-oriented and more car-dependent context, SMM may be mainly used by those who already have a cycling habit or lifestyle.

In all three study areas, SMM users were found to be more likely to have a PT season ticket. As we found SMM users also use public transport frequently, the results together imply that SMM is likely a complement to public transport, either as a connecting solution or as an alternative when public transport is unavailable (Luo et al., 2021; van Kuijk et al., 2022). We found that people in SMM user classes tend to travel longer on weekdays and/or weekends, which again confirms that SMM may be used by those who have diverse travel needs to support their multimodal travel. Still, the occasional SMM user class in Greater Manchester show different travel habits than other SMM user classes, as this group of people travel shorter on both weekdays and weekends. This indicates that they do not need to travel long distances, but they still rely on car use, implying the potential of SMM to replace short-distance car trips.

According to the one-way ANOVA tests, in Utrecht and Greater Manchester, there were no significant differences in neighbourhood spatial characteristics between classes. In Malmö, compared to SMM users, non-SMM users who use PT as the major transport option tend to live in neighbourhoods closer to the city centre and train station, and non-SMM users who primarily use cars tend to live in neighbourhoods farther from the city centre and train station. As a result of the post-hoc analysis (see Appendix A), in Greater Manchester, people in the two SMM user classes tend to live in neighbourhoods with higher walking or cycling way density. While in Utrecht and Malmö, no significant differences were found between SMM user classes and non-user classes. Therefore, it can be inferred that in Greater Manchester, where driving is more dominant and cycling is less common, better cycling facilities and higher accessibility may encourage SMM use and facilitate multimodality. While in Utrecht and Malmö, where cycling facilities are more developed and extensive, the within-city differences in the density of bike lanes are not related to differences in residents' travel patterns.

In sum, users of different travel patterns differ in their personal demographics and personal travel characteristics, while the spatial differences between the neighbourhoods in which they live are not obvious. In all study areas, people who take more social responsibilities and have more travel needs are more likely to frequently use various SMM and existing transport modes, and SMM is more likely to be used by those who also have a public transport season ticket.

5.3. Policy implications: integrate SMM to existing transport systems in different urban contexts

Based on our findings, we recommend that policies aiming to increase SMM usage and promote multimodality should prioritise the integration of SMM into existing transport systems across different urban contexts.

In all three study areas, we observed that people who frequently use multiple SMM and other existing transport modes tend to be more socially active. This includes having more work engagements (full-time employees) and more caregiving responsibilities (parents of young children), which may result in greater travel needs. To better support these users, we recommend cities design SMM systems that cater to both solo and group travel, particularly for travelling with children, as frequent SMM users are more likely to live with children and may need child-friendly travel options. SMM vehicles should be designed to safely accommodate children, with insurance options that reflect this need. For example, shared (e-)cargo bikes, available in several Dutch cities, can serve as a convenient and safe means of transporting children. Other SMM modes like shared (e-)bikes could also be equipped with features like child seats. Such shared bikes are now available in China with a gravity sensor to ensure that the child is of a suitable weight to be transported. Other cities and SMM providers could consider implementing such inclusive design elements. Additionally, we suggest cities develop tailored Mobility-as-a-Service (MaaS) products for regular commuters and those who often travel with children. Since this group frequently uses various SMM and existing transport modes, digital integration of these travel options may streamline their multimodal travel. For example, MaaS products could enable seamless transfers between public transport and SMM, offer discounts for using multiple modes in a certain time frame (e.g. in an hour), and provide reduced fares for travelling with children (Butler et al., 2021).

In Utrecht and Greater Manchester, we found occasional SMM users often rely on car as well. Since they use both micromobility and public transport, better integration of SMM and public transport, alongside improvements in public transport quality, could encourage them to replace some car trips with multimodal trips combining SMM and public transport use (Montes et al., 2023; Oeschger et al., 2020). Still, the findings on occasional SMM users' travel time indicate that in Utrecht, occasional SMM users may need to travel longer distances and thus use cars more often, whereas in Greater Manchester, occasional SMM users are car-dependent even without needing to travel longer distances. Since inter-city travel (even commuting) is common in the Netherlands, and Utrecht is well-connected with other cities by railway, in Utrecht, enhancing SMM access to railway stations may attract SMM users to replace long-distance car trips with a combination of SMM and train travel. Despite the long-standing bike-sharing services offered by the Dutch national railway, more diverse SMM modes could be introduced in railway station areas, such as electric SMM vehicles, in partnership with private providers. In Greater Manchester, however, the focus should be on encouraging SMM as an alternative to short-distance car trips, and we will explore specific solutions for this later in this Section.

For more cycling-oriented cities like Utrecht, SMM could be an effective tool to shape car drivers' cycling habits. Most residents in Utrecht own private bikes, but frequent SMM users tend to have no private bikes and use cars more frequently, so they are less sustainable in daily travel than the average travellers. In this sense, the city could foster a passion for micromobility, whether shared or private, by offering incentives. For example, providing free rides after a set number of trips or a points system for ride credits may encourage more frequent SMM use, potentially leading SMM users to adopt cycling as a lifestyle or purchase a private (e-)bike (Delbosc & Thigpen, 2024).

For car-dependent cities like Greater Manchester, expanding cycling infrastructure and improving the coordination between SMM and train systems may increase SMM usage and reduce car dependency. We found that residents of neighbourhoods with more bike lanes are more likely to use both SMM and private micromobility. Given the limited bike path coverage in the city, expanding and densifying the bike lane network may effectively promote micromobility including SMM. Additionally, public transport, particularly trains, competes with cars in Greater Manchester, as a higher modal share of one is always associated with a lower modal share of the other. Integrating SMM into first- and last-mile planning may improve access to train stations, further reducing car trips in favour of combined SMM and train use.

For transit-oriented cities where SMM is still in its early stages, like Malmö, SMM may have the potential to support multimodal travellers who primarily use diverse public transport options. Our findings suggest that women, students, and low-income people are more likely to be multimodal travellers who primarily use public transport but do not use SMM. Cities could explore ways to motivate these groups to adopt SMM, which may help them travel more easily. Raising awareness through informational campaigns about SMM in transit hubs, such as signage in bus stops in the city centre and in train stations may help attract these users, who tend to live closer to the city centre and train stations. Additionally, with the potential popularity of SMM, improving road environments to protect SMM users is crucial. Expanding the coverage of 30 km/h zones could be an effective measure to enhance safety, as this has not yet been implemented in Malmö.

6. Conclusion

This study comprehensively investigated the use of different SMM modes and existing transport modes in three European cities. Using Latent Class Analysis, we identified four patterns of modal combinations in each city. There are three key findings. First, SMM users are more multimodal in their daily travel, which demonstrates that SMM has the potential to promote multimodality. Second, users of different travel patterns mainly differ in their personal characteristics and mobility options, but less so in where they live within the city, which implies that cities can tailor the interventions to different traveller segments (Dacko & Spalteholz, 2014), but still need to consider where to deploy the SMM services and ensure it is accessible everywhere. Third, the travel patterns and user characteristics vary in cities with different urban contexts and mobility systems. Specifically, in more cycling-oriented cities, SMM shows higher potential to promote multimodality because it is used as a supplementary by those who do not have a personal bike, but in more car-dependent cities, SMM seems to be mainly used by those who already have cycling habits as an alternative to private bikes. Therefore, a challenge is proposed to those car-dependent cities to attract more people to use micromobililty both in the forms of private or shared. Our findings suggest cities collaborate with both transit authorities and SMM companies to better integrate public transport and SMM, which may induce a shift from car use to the combined use of public transport and SMM.

The present study still has limitations and future research may extend the present study in the following ways. First, we use a cross-sectional dataset to analyse the modal combination of SMM and existing transport modes at a one-time point, but since SMM is still at an early stage and keeps penetrating people's daily travel, it is imperative to investigate how these interactions change with the penetration of SMM. Second, we mainly investigate who and where the users of different travel patterns are. To better understand and integrate SMM into the existing transport modes and support multimodal travel, travellers' experiences on the travel patterns can also be an important reference and deserve research attention.

CRediT authorship contribution statement

Xingxing Fu: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Dea van Lierop:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Dick Ettema:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was supported by JPI Urban Europe via national grants from: NWO, Netherlands, Grant [438-21-434]; UK, Economic and Social Research Council (ESRC) [ES/W000547/1]; Sweden, Energimyndigheten, Dnr 2021-001267, [51970-1]. We would also like to thank the China Scholarship Council for providing the PhD scholarship.

Appendix A. Results of multinomial logistics regression

	NL					UK					SE		
	Ref: Class 1 (*F-MM*)			Ref: Class 2 (*O-AM*)		Ref: Class 1 (*F-MM*)			Ref: Class 2 (*O-CM*)		Ref: Class 1 (*F-MM*)		
	Class 2	Class 3	Class 4	Class 3	Class 4	Class 2	Class 3	Class 4	Class 3	Class 4	Class 2	Class 3	Class 4
	O-AM	*N-AP*	*N-C*	*N-AP*	*N-C*	*O-CM*	*N-CP*	*N-C*	*N-CP*	*N-C*	*N-AC*	*N-PM*	*N-C*
Personal demographic factors													
Gender (ref: Man)													
Woman or non-binary	−0.043	0.390	0.952	0.432	**0.995***	0.526	**1.220*****	**1.330*****	**0.694****	**0.804****	0.108	0.203	0.067
	0.891	**1.812****	**2.230*****	**0.921***	**1.339*****	0.098	**0.893****	**1.279*****	**0.795*****	**1.181*****	0.552	0.515	**0.949****
Age													
	−0.545	−0.758	−0.554	−0.213	−0.009	−0.223	−0.243	−0.245	−0.019	−0.021	0.131	−0.034	−0.103
Household income													
	0.173	0.472	0.244	0.299	0.070	−0.080	0.056	0.052	0.136	0.132	−0.041	0.060	−0.281
Education level													
	−1.877*	**−2.701*****	**−1.879****	−0.823	−0.002	−0.082	−0.750	−0.481	**−0.668***	−0.399	−0.754	−0.575	−0.634
Living with children													
Employment status (ref: Full-time)													
Part-time (self-employed)	**1.557***	**1.970****	**2.471*****	0.413	0.913	0.268	0.551	0.841	0.283	0.574	0.083	0.040	0.193
	−1.887	−0.577	−0.958	1.311	0.930	−0.160	0.466	−0.421	0.626	−0.261	0.115	0.697	−0.103
Student													
	−5.172***	**18.026*****	**18.477*****	**21.177****	**21.627*****	**22.463*****	**21.564*****	**21.092*****	−0.899	−1.371	0.677	−0.026	0.536
Retired													
	−3.622**	−1.771	−1.047	1.852	**2.576***	−1.012	−0.105	−0.478	0.906	0.534	0.054	0.186	0.135
Unemployed													
Personal travel factors													
Having a driver's license	**−4.576***	**−4.193***	**−4.310***	0.383	0.266	0.227	−0.647	−0.218	**−0.875***	−0.445	−0.257	−0.473	−0.216
Car ownership (ref: no car)													
Personal car	−0.461	−1.561	−0.247	−1.100	0.214	−0.328	**−1.600****	−0.520	**−1.272*****	−0.192	0.312	−0.659	**1.302***
	0.632	1.005	0.643	0.373	0.012	0.256	−0.848	−0.930	**−1.104****	**−1.185***	−0.038	−0.371	1.015
Household car													
	2.438**	**2.347*****	**2.282*****	−0.091	−0.157	**−0.755***	**−1.366*****	**−1.670*****	**−0.611***	**−0.915****	0.709	−0.052	−0.354
Having a private bike													
	−0.525	−0.129	**−1.227*****	0.396	**−0.702****	−0.234	**−0.481****	**−1.215*****	−0.246	**−0.981*****	**−1.438*****	0.263	**−1.628*****
PT season ticket subscription													
	0.322	0.316	0.045	−0.006	−0.277	0.059	−0.165	−0.215	−0.224	−0.274	**−0.351***	−0.288	**−0.407***
Weekday travelling hours													
	−0.410	−0.524	**−0.707***	−0.114	−0.297	**−0.328***	−0.217	−0.176	0.110	0.152	−0.097	−0.082	−0.244
Weekend travelling hours													
Neighbourhood spatial factors													
Population density (1000/km^2)	−0.579	−0.710	−0.871	−0.131	−0.292	−0.109	−0.422	−0.263	−0.313	−0.153	−0.586	−1.499	−0.876
	−0.639	−0.575	−0.411	0.064	0.228	−0.272	**−0.652***	−0.599	−0.380	−0.327	0.741	1.039	1.142
Distance to the city centre (km)													
	−0.296	−0.221	−0.400	0.076	−0.104	−0.076	−0.274	−0.396	−0.199	−0.320	−0.510	−0.963	−0.915
Distance to the train station (km)													
	−0.282	−0.151	0.282	0.131	0.563	0.076	−0.059	−0.354	−0.135	−0.431	0.466	0.807	0.480
Public transport density (1000/km^2)													
	0.455	0.263	0.498	−0.192	0.044	−0.321	−0.357	**−0.488***	−0.037	−0.168	0.124	−0.594	1.107
Cycling way density (km/km^2)													
	−0.407	−0.160	−0.524	0.247	−0.117	0.139	−0.293	−0.122	**−0.432****	−0.261	0.477	2.034	−0.809
Walking way density (km/km^2)													
	0.109	0.392	0.525	0.283	0.416	0.063	0.073	0.072	0.010	0.009	−0.016	0.031	0.927
Percentage of roads with speed limit of 30 km/h or less (32 km/h for UK) (%)													

Note: In each model, the travel pattern where SMM is used frequently or occasionally was used as the reference group.
Coefficients are reported and all significant coefficients are in boldface.

*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.

Data availability

The authors do not have permission to share data.

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